Segmentation of Coronary Artery Using Region-Based Level Set with Edge Preservation

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In this paper, we present a level set method for segmentation of coronary artery. The proposed method is a region-based method with the ability of edge preservation. In the proposed method, local intensity information is introduced into the level set formulation where the bias field is estimated by a linear combination of a given set of orthogonal basis functions. The intrinsic regularization mechanism of the proposed method is used to ensure regularity of the level set function and smoothness of the zero-level contour and reduce miss-and over-segmentation caused by the noise. We evaluate the proposed method on public images from the Coronary Artery Stenoses Detection and Quantification Evaluation Framework, a satellite event of MICCAI 2012. Experimental results and comparison analysis demonstrate that segmentation results of the proposed method are close to that from three blinded observers.

Keywords: Level Set, Bias Estimation, Coronary Artery Segmentation.

1. INTRODUCTION

Coronary Artery Stenosis (CAS) is currently almost the first cause of death in the US and the leading cause of death worldwide. The human heart and coronary arteries can be imaged by multi-detector computed tomography (CT). After injection of contrast agent (computed tomography angiography, CTA), relatively reliable imaging of the coronary arteries can be achieved, for example, soft stenosis will be a little dark, whereas calcified stenosis will be more bright. However, as shown in Figure 1, it is very challenging to detect and grade coronary stenosis in CTA images due to the varying image quality. Firstly, artifacts caused by irregular heartbeat and respiratory movement are encountered frequently although beta blockages are usually used to reduce the effect of heart rate in routine. Secondly, staircase reconstruction artifacts, resulted by gated or modulated protocols, further complicate the analysis. Finally, in the distal parts, coronary arteries extends only a few voxels in diameter, following long and treacherous paths.

To detect and quantify CAS accurately, segmentation of coronary artery from cardiac CTA images is very important. Although manual segmentation can be performed by trained radiologists, it is labor-intensive, time-consuming, and sensitive to intra- and inter-observer variability. However, only a few of semi-automatic or fully automatic methods have been proposed to segment coronary artery in the literature due to the weak boundary nature and intensity inhomogeneity as shown in Figure 1. Two comprehensive reviews of 3D vessel segmentation can be found in Refs. [10, 11].

In this paper, we propose a level set method that combines edge and local intensity information in a variational level set formulation. By resolving the gradient flow equation of our level set function, coronary artery lumen segmentation can be accurately achieved. We take the minimal value inside our level set function as the refined centerline by taking into account the regularization of our level set function. After the segmentation and centerline extraction, we detect and quantify stenosis from a cross sectional curve along the centerline by computing a weighted average of the area and the shortest diameter of each cross sectional curve.

The rest of this paper is organized as follows. We describe the proposed method in Section 2. We then give experimental results of the proposed method in Section 3. We discuss the proposed method and conclude this paper in Section 4.

2. METHOD

Given an cardiac image \( I \) with weak boundary nature defined on a continuous domain \( \Omega \subset \mathbb{R}^2 \), its intensities can be viewed as a function \( I: \Omega \rightarrow \mathbb{R}^2 \). As well known, the intensity of the observed image \( I \) with the intensity inhomogeneity at location
A normalized even function with the property \( \lim_{u \to v} K(u) = K(v) \), and the bias field can be viewed as a product of the bias field \( b \) and the true image \( J \) at this location, i.e.,

\[
I(x) = b(x) J(x) + n(x)
\]

where \( n \) is additive noise with zero-mean. The true image \( J \) characterizes an intrinsic physical property of objects being imaged. It ideally takes a specific intensity nearby the coronary artery \( c_i \) for objects inside the lumen and \( c_o \) for objects outside the lumen. That is to say, the true image \( J \) takes 2 distinct constant values \( c_i \) and \( c_o \) approximately inside and outside the lumen, respectively. As well known in the literature, the bias field \( b \) is usually assumed to be slowly and smoothly varying. The problem of image segmentation and bias correction is therefore considered as finding the specific intensity constants \( c_i \) and \( c_o \) and estimating the bias field \( b \).

2.1. Locally Regional Energy

To ensure the slowly and smoothly varying property of intensity inhomogeneity, the bias field can be simulated by a given set of smooth orthogonal basis functions \( g_1, g_2, \ldots, g_M \) with weighting coefficients \( w_1, w_2, \ldots, w_M \), i.e.,

\[
b(x) = \mathbf{w}^T G(x)
\]

where \((\cdot)^T\) is the transpose operator, \( G(x) \) and \( \mathbf{w} \) are column vectors defined by \( G(x) = (g_1(x), g_2(x), \ldots, g_M(x)) \) and \( \mathbf{w} = (w_1, w_2, \ldots, w_M)^T \), respectively.

Let \( O_y = \{ x : |x-y| \leq \rho \} \) be a circular neighborhood with a radius \( \rho \) centered at the given point \( y \in \Omega \). If the neighborhood is small enough, the bias field in the neighborhood can be obviously ignored. That is, \( b(x) \approx b(y) \) for \( x \in O_y \). Thus, we define

\[
\mathcal{E}_y = \lambda_1 \int_{O_1} K(x-y)|I(x) - \mathbf{w}^T G(x)c_i|^2 \, dx + \lambda_2 \int_{O_2} K(x-y)|I(x) - \mathbf{w}^T G(x)c_o|^2 \, dx
\]

where \( \lambda_1 \) and \( \lambda_2 \) are positive weighting coefficients and \( K \) is a normalized even function with the property \( K(u) \leq K(v) \), if \( u > v \), and \( \lim_{|u| \to \infty} K(u) = 0 \), which can be seen as a window function such that \( K(x-y) = 0 \) for \( x \not\in O_y \).

To ensure \( \mathcal{E}_y \) is minimized for all \( y \in \Omega \), we minimize the integral of \( \mathcal{E}_y \) with respect to \( y \) over the entire image domain \( \Omega \) and define

\[
\mathcal{E} = \int \mathcal{E}_y \, dy = \int (\lambda_1 \int_{O_1} K(x-y)|I(x) - \mathbf{w}^T G(x)c_i|^2 \, dx) \, dy + \int (\lambda_2 \int_{O_2} K(x-y)|I(x) - \mathbf{w}^T G(x)c_o|^2 \, dx) \, dy
\]

2.2. Level Set Representation

Let \( \phi : \Omega \to R \) be a level set function defined on \( \Omega \). We denote the 0-level set contour of the level set function \( \phi \) by \( C \), i.e., \( C \triangleq \{ x : \phi(x) = 0 \} \), which is used as to be the segmentation contour. This contour separates the image domain into two regions: \( \Omega_1 \) (inside the artery lumen) and \( \Omega_2 \) (outside the artery lumen), which are regarded as inside and outside of the 0-level set contour \( C \), respectively. We let the level set function \( \phi \) take negative and positive values inside and outside the 0-level set contour \( C \) in this paper, i.e., \( \Omega_1 \triangleq \{ x : \phi(x) < 0 \} \) and \( \Omega_2 \triangleq \{ x : \phi(x) > 0 \} \). Thus, membership functions of the regions can be written as \( M_1(\phi(x)) = 1 - H(\phi(x)) \) and \( M_2(\phi(x)) = H(\phi(x)) \), where \( H \) is the Heaviside function. We rewrite the energy \( \mathcal{E} \) described in Eq. (4) into the following level set formulation:

\[
\mathcal{E} = \int \left( \lambda_1 \int_{\Omega_1} K(x-y)|I(x) - \mathbf{w}^T G(x)c_i|^2 \, dx \right) M_1(\phi(x)) \, dx + \int \left( \lambda_2 \int_{\Omega_2} K(x-y)|I(x) - \mathbf{w}^T G(x)c_o|^2 \, dx \right) M_2(\phi(x)) \, dx
\]

It is obvious that the energy \( \mathcal{E} \) is a function of variables the level set function \( \phi \), the vector \( \mathbf{c} = (c_i, c_o) \), and the weight coefficients of the basis functions. Therefore, we rewrite the energy \( \mathcal{E} \) as

\[
\mathcal{E}(\phi, \mathbf{w}, \mathbf{c}) = \int \lambda_1 e_1(x) M_1(\phi(x)) \, dx + \int \lambda_2 e_2(x) M_2(\phi(x)) \, dx
\]

where \( e_1(x) = \int K(x-y)|I(x) - \mathbf{w}^T G(x)c_i|^2 \, dx \) and \( e_2(x) = \int K(x-y)|I(x) - \mathbf{w}^T G(x)c_o|^2 \, dx \).

The energy \( \mathcal{E}(\phi, \mathbf{w}, \mathbf{c}) \) defined in Eq. (6) is used as the data term of the following energy functional

\[
F(\phi, \mathbf{w}, \mathbf{c}) = \mathcal{E}(\phi, \mathbf{w}, \mathbf{c}) + \mu \mathcal{P}(\phi) + \nu_1 \mathcal{L}(\phi) + \nu_2 \mathcal{L}_x(\phi)
\]

where \( \mathcal{P}(\phi) \) is the regularization term used here to maintain the regularity of the level set function, \( \mathcal{L}(\phi) \) and \( \mathcal{L}_x(\phi) \) are arc length terms used to smooth the 0-level set contour of the level set function \( \phi \), and \( \mu, \nu_1, \) and \( \nu_2 \) are positive weighting coefficients. The definitions of these regularization terms are given below.

The following regularization term \( \mathcal{P}(\phi) \) is used to preserve the stability of the level set function \( \phi 

\[
\mathcal{P}(\phi) = \frac{1}{2} (|\nabla \phi(x)| - 1)^2 \, dx
\]

Note that this term was first introduced by Li et al. in\(^12\) to intrinsically maintain the regularity of the level set function during its evolution.
The arc length terms are defined by
\[ \mathcal{L}(\phi) = \int \delta(\phi(x)) |\nabla \phi(x)| \, dx \] (9)
and
\[ \mathcal{L}_k(\phi) = \int g(\delta(\phi(x))) |\nabla \phi(x)| \, dx \] (10)
respectively, where \( \delta \) is the derivative function of Heaviside function \( H \), \( g \) is an edge indicator function defined by
\[ g \triangleq \frac{1}{1 + |\nabla G_\sigma * I|^2} \] (11)
where \( G_\sigma \) is a Gaussian kernel with a standard deviation \( \sigma \).

Note that the local data energy term \( \mathcal{E} \) is used in this paper as a regional force to lead the zero contour moves to the boundaries. The arc length term \( \mathcal{L}_k(\phi) \) with edge indicator \( g \) is used in the level set formulation as an intrinsic force to lead the zero contour towards to desired edges.

2.3. Energy Minimization

The energy minimization is achieved by an iterative process where the energy functional \( F(\phi, w, c) \) with respect to each of its variables is minimized in each iteration by giving the other two updated in previous iteration. The solution to minimize the energy functional \( F(\phi, w, c) \) with respect to each of its variables \( \phi, w, \) and \( c \) are given as follows.

For fixed \( w \) and \( c \), we minimized the energy functional \( F(\phi, w, c) \) with respect to \( \phi \) using the standard gradient descent method and obtain
\[
\frac{\partial \phi}{\partial t} = \delta(\phi)(\lambda_1 \epsilon_1 - \lambda_2 \epsilon_2) + \mu \left( \nabla^2 \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right) + \nu \delta(\phi) \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) + \nu_i \delta(\phi) \text{div} \left( g \frac{\nabla \phi}{|\nabla \phi|} \right) \] (12)

For fixed \( \phi \) and \( c \), we minimized the energy functional \( F(\phi, w, c) \) with respect to \( w \). By solving the equation \( \partial F/\partial w = 0 \), we obtain
\[ w = A^{-1}v \] (13)
where \( A \) is an \( M \times M \) matrix given by
\[ A = \int (K * (\lambda_1 c_1^2 M_1(\phi) + \lambda_2 c_2^2 M_2(\phi))) (y) G(y) G^T(y) \, dy \] (14)
and \( v \) is an \( M \)-dimensional column vector given by
\[ v = \int (K * (I(\lambda_1 c_1^2 M_1(\phi) + \lambda_2 c_2^2 M_2(\phi))) (y) G(y) \, dy \] (15)
For fixed \( \phi \) and \( w \), the energy functional \( F(\phi, w, c) \) can be minimized by the optimal \( c \) with
\[ c_i = \frac{\int I(x) M_1(\phi(x))(K * (w^T G))(x) \, dx}{\int M_1(\phi(x))(K * (w^T G)^2)(x) \, dx} \] (16)
and
\[ c_o = \frac{\int I(x) M_2(\phi(x))(K * (w^T G))(x) \, dx}{\int M_2(\phi(x))(K * (w^T G)^2)(x) \, dx} \] (17)

2.4. Implementation

In this paper, the stepped Heaviside function \( H \) is approximated by a smoothed Heaviside function \( H_\epsilon \), defined by
\[ H_\epsilon = \frac{1}{2} \left( 1 + \frac{2}{\pi} \arctan \left( \frac{x}{\epsilon} \right) \right) \] (18)
It is obvious that the derivative of \( H_\epsilon \) can be written as
\[ \delta(x) = H_\epsilon' = \frac{1}{\pi} \frac{e}{x^2 + \epsilon^2} \] (19)
In implementation of the proposed method, the following Gaussian kernel function is chosen as function \( K \):
\[ K_n(u) = \frac{1}{(\sqrt{2\pi}\sigma)^n} e^{-|\mu|^2/2\sigma^2} \] (20)
where \( n \) is the dimension number of variable \( u \) and \( \sigma \) is the standard deviation. We set \( \sigma = 3 \) in this paper.

In this paper, 15 orthogonal four order Legendre polynomial functions are used as the basis functions, i.e., \( M = 15 \). The implementation of the proposed method can be straightforwardly expressed as follows.

- Step 1: Initialize \( w \) and \( \phi \).
- Step 2: Update \( c \) using Eqs. (16) and (17).
- Step 3: Update \( \phi \) in Eq. (12).
- Step 4: Update \( w \) in Eq. (13).
- Step 5: Check the convergence criterion. If convergence is reached or the iteration number exceeds a predetermined number, stop the iteration; otherwise, go to Step 2.

The convergence criterion used in Step 5 is \( |e^{(n-1)} - e^{(n)}| < 0.001 \), where \( e^{(n)} \) is the vector \( e \) updated in Step 2 at the \( n \)-th iteration.

3. EXPERIMENTAL RESULTS

The proposed method has been tested on public images from the Coronary Artery Stenoses Detection and Quantification Evaluation Framework (http://coronary.bigr.nl/stenoses/index.php), which was a satellite event of MICCAI 2012. For the framework, 48 CTA image cases of symptomatic patients are used. For each patient, three experts manually annotated the coronary artery boundaries of all diseased segments as well as three random healthy segments. Eighteen image cases with the associated reference segmentations are used as the training dataset. The

![Fig. 2](image_url) Segmentation results of the proposed method on one image case with calcific stenosis. Sectional images are given in the first row, whereas the visualization results of the segmentation are given in the second row.
remaining thirty image cases are considered as testing set with no references shared with the participants for this dataset.

To evaluate segmentation results of the participant methods quantitatively, Root Mean Squared Distance (RMSD) and the Dice Similarity Coefficient (DSC) are computed and compared. The RMS measures the deviation of the obtained segmentation result $B$ from the reference standard $A$, defined by

$$\text{RMSD} = \frac{\sum_{a,b \in A,B} d(a, b)}{|A|}$$

where $d(a, b)$ is the Euclidean distance between $a$ and $b$. Note that RMSD is given in mm, a lower value indicating a better match between $A$ and $B$. Let $\cap$ be the intersection operator, it is well known that

$$\text{DSC} = \frac{2|A \cap B|}{|A| + |B|}$$

Note that DSC values are in the interval of $[0, 1]$ with a higher one indicating a better match between $B$ and $A$.

Segmentation results of the proposed method in this paper are obtained with $\mu = 1.0$, $\lambda_1 = \lambda_2 = 1.0$, $v_1 = v_2 = 0.5$, $\delta = 5.0$, and $\epsilon = 1.5$. The parameter settings are determined from the training dataset. To view the results intuitively, visualization results of the proposed method on one image case with calcific stenosis are given in Figure 2. As shown in the sub figure where the coronary artery is partially enlarged, the stenosis is obvious there. Tables I and II show quantitative comparison of segmentation results of the proposed method with methods participated in the framework and the blinded observers on the training and testing datasets, respectively. It is obvious that segmentation results of the proposed method are close to the results from the blinded observers and the proposed method located in the middle of the methods participated in the framework for most of the evaluation metrics.

### 4. DISCUSSION AND CONCLUSIONS

We proposed a region-based level set method for segmentation of coronary artery. An edge based energy term is introduced to ensure reserved ability of the proposed method in edge recognition. Experiments and comparison demonstrate that the proposed method is good enough to replace blinded observers. But this is a preliminary result of our work and we would like to improve our result in the future.

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### References and Notes


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